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Framework for Smart Transactive Energy in Home-Microgrids Considering Coalition Formation and Demand Side Management

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Abstract

The concept of Transactive energy (TE) been adapted in the regulation of electricity market within the context of economic planning and control for grid reliability enhancement. The objective is to improve productivity and participation of the players in the market that is composed of distributed energy resources (DER). The main goal of implementing a market structure based on TE is to secure permission for the market players so that they could attain a higher payoff. In this study, an optimization-based algorithm in which an objective function premised on economic strategies, distribution limitations and the overall demand in the market structure is proposed. The objective function is solved for near global optima using four heuristically guided optimization algorithms. The proposed algorithm which ensures that none of the independent players has priority and/or advantage over others, emphasizes optimum use of electrical/thermal energy distribution resources, while maximizing profit for the owners of the home Microgrids (H-MGs). Reduction in

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the market clearing price (MCP) for further participation and the response of the consumers' responsive loads are also considered in the study. The feasibility of the proposed algorithm is validated in a coalition formation scenario among the existing H-MGs. Results show an increase in the profit attained, enhanced system reliability and a reduction in the electricity cost of the consumers.

Keywords: Transactive energy, home microgrids, coalition formation, responsive load, electricity market

1 Nomenclature

Acronyms

AEL	aggregated electrical load
ATL	aggregated thermal load
CHP	combined heat and power
DR	demand response
DR+, DR-	amount of responsive load demand (RLD) that goes/come from/to other time period to/from t
DW	dish washer
DER	distributed energy resources
DSO	distributed system operator
EES	electrical energy storage
ESP	electrical solar panel
EV	electrical vehicle
GB	gas boiler
HHW	heat and hot water
H-MG	home microgrid
MCP	market clearing price
MO-TE	market operator based on transactive energy
MG	Microgrid
NG	natural gas
PV	photovoltaic
REF	refrigerator

RET	retailer
RET+/RET-	buying/ selling power from/to H-MG i / the retailer
SBP	system buy price
SSP	system sell price
SOC	state-of-charge
TD	thermal dump
TES	thermal energy storage
TSP	thermal solar panel
TE	transactive energy
Indices	
$E/h/t/i, i \in \{1, 2, \dots, n\}$	electricity/ heat/ time steps/ H-MG number
$j \in \{CHP, GB, TSP\}$	thermal DERs
$k \in \{ESP, CHP\}$	electrical DERs
$m \in \{DW, EV, REF, AEL\}$	electrical consumers
$p \in \{HHW, ATL, TD\}$	thermal consumers
Constant values	
$\underline{SOC}^x, \overline{SOC}^x, \bar{P}_{e/h}^x, \underline{P}_{e/h}^x$	minimum values/ maximum SOC/ power during X charging and discharging mode
$x \in \{ES+, ES-, EV+, EV-, TES+, TES-\}$	
E_{Tot}^x	total value of X capacity

$\underline{T}^y, \bar{T}^y$	maximum/ minimum value of y temperature
$y \in \{\text{REF}, \text{HHW}\}$	
$\bar{P}_{e/h}^j, \underline{P}_{e/h}^j$	minimum values/ maximum electrical thermal power j
$T_{\text{INI}}^y, T^{\text{RED}}, T^{\text{INC}}$	initial temperature/ the amount of temperature reduction each time the REF compressor is turned on/ the amount of temperature increase each time HHW is turned on
$\zeta_{e/h}^j$	electrical and thermal efficiencies j
$\underline{T}^{\text{HHW}}, \bar{T}^{\text{HHW}}$	maximum and minimum values of temperature
$\bar{E}^x, \underline{E}^x$	maximum and minimum values of energy in x
$\bar{E}^z, \underline{E}^z$	maximum and minimum values of z price bids
$z \in \{j, k, m, l\}$	
π_t^{NG}	natural gas price

Constant values

$\tilde{\lambda}_t^{\text{MCP}}$	MCP prediction value during each time interval t (£/kWh)
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Decision variables

$X_t^{\text{Ret}}, X_t^{\text{ES}}, X_t^{\text{TES}}, X_t^{\text{DR}}$	binary variable of retailer, electrical energy storage, thermal energy storage, demand response
$P_{t,e}^m, P_{t,h}^p$	Consumed electrical/ thermal power by l/ m at time t
$P_{t,e}^j, P_{t,h}^k$	Electrical/ thermal power generated by k/ j at time t
$\pi_{t,e}^z, \pi_{t,h}^z$	Electrical/ thermal price bids by z at time t
$P_{t,e}^{\text{Ret}+j}, P_{t,e}^{\text{Ret}-j}$	The electric power sold/ bought by H-MG i to/from the retailer
$\lambda_{t,s}^{\text{MCP}}$	Market clearing price by using the S optimization method (£/kWh)
	S=1: particle swarm optimization (PSO)
	S=2: harmony search (HS)
	S=3: differential evolution (DE) algorithm
	S=4: bat algorithm (BAT)

1. Introduction

The ever-increasing global demand for electricity, coupled with the fast depletion of the fossil fuels, as well as the environmental impact of burning these fuels

9 has led to the present restructured electricity industry [1]. The aforementioned fac-
10 tors have led to emergence of new technologies for generation, distribution, energy
11 transfer and consumption as well as the need for optimum energy management
12 and energy efficiency improvements [2–5]. To this end, smart grids, evolved from
13 upgrading of the existing electricity grids with these new technologies and services
14 which make them more reliable, optimal and environmentally friendly, have been
15 proposed [6–9]. In contrast to the traditional power grids, smart grids are develop-
16 ing rapidly with a structure based on home microgrids (H-MG) with certain desir-
17 able features such as self troubleshooting and self repair, as well as comprehensive
18 control [10, 11].

19 In developing smart grids, the concept of Transactive energy (TE) has become
20 indispensable to enable further participation of different players in the power indus-
21 try. This concept ensures the security of supply and reduces the need for exchange
22 of personal information among the players [10–22]. Furthermore, TE is a combi-
23 nation of economic and control techniques with the aim of increasing the system
24 efficiency and reliability.

25 The TE concept is also executable in non-concentrated electrical energy compet-
26 itive markets [19]. One of the advantages of TE is that it allows the consumers to be
27 supplied from any resource of their choice. The framework of the market structure
28 includes drivers such as: 1) advancement in technology and customer knowledge,
29 2) need to enhance system productivity 3) depletion of the fossil fuels, 4) quest for
30 more reliable and flexible systems, 5) need for a reduction in air pollution and, 6)
31 further participation of the players in the market [10, 19, 23].

32 With the energy transfer concept, TE systems help grid reliability and improve
33 both efficiency and interaction among system stakeholders [24]. The consumers’
34 participation in the demand response (DR) load program has a significant role in the
35 market structure based on TE since DR is one of the possible strategies to maintain a
36 balance between the supply and demand in H-MGs. The DR program is designed to
37 shift load demands away from system peak demand towards non-peak intervals. In
38 [22], the effect of DR planning was investigated over the market dynamics based on
39 price. The efficiency of the electricity market and the power grid was demonstrated

40 in the study.

41 It was shown in [24, 25] that implementing DR also removes the problem of
42 predicting flexible loads and the probability of the customer's response to price
43 in the retail market. In the market structure based on TE, the retailers act as a
44 bridge between wholesalers and small customers. On the other hand, the H-MGs
45 are a part of the smart grid on the side of the consumer. H-MGs are considered as
46 another active player in the market structure [26–32]. In the presence of electric
47 vehicles (EV), the studies presented a non-concentrated control method in a bid to
48 minimise the cost of the DERs in the H-MG to reduce the distribution power loss.
49 In this method, a price coordinator was presented to assess the mutual effect of the
50 distribution system operator (DSO) and the collectors in a smart grid.

51 In [33, 34], an H-MG incorporating a photovoltaic (PV) system showed the re-
52 sponsiveness of strategies to price for charging EV. While it increases the strength
53 of short-term demand, it significantly reduces the costs of energy for the customers.
54 A solution for the coordinated execution of DR in H-MG by learning the predic-
55 tion of power demand based on life style and social-environmental factors was pre-
56 sented in [33]. The other important issue in a market based on the TE structure is
57 the possibility of one player forming a coalition with other players. In [35] the H-
58 MGs, both grid-connected and off grid configurations, participated in coalition with
59 each other in a market structure. Simulation results showed significant reduction
60 in power losses and a cost reduction in both modes. In [36], it was demonstrated
61 that cooperative algorithms are approximately one hundred percent more profitable
62 than non-cooperative algorithms. In the same vein, using coalition game theory to
63 reduce the power loss in transfer lines, could lead to a reduction in the cost.

64 The following deficiencies regarding creation of an energy management system
65 for multiple H-MGs based on TE concept have been identified from previous work
66 and highlighted in this paper:

- 67 • Lack of an algorithm for exchange of energy and the impossibility of supplying
68 the consumer load demand through the generating resources of other H-MGs
69 [10, 11, 36–41];

- 70 • Non-availability of a demand response program to calculate the MCP [10, 11,
71 17–22, 35, 42–46].
- 72 • Non-existence of optimization algorithms for solving and implementing the
73 optimum clearance of the market process and obtaining pay-off for all market
74 players [18, 20, 34, 47, 48].
- 75 • Inability to determine the strategy and behaviour of residential customers as
76 prosumer for participating in the market [21, 49–52].
- 77 • Lack of an algorithm to achieve the overall profit of the players and address
78 the stochastic behaviour of the players in the optimization process [19, 33,
79 53–55].

80 In this paper, improved versions of the popular optimization techniques, includ-
81 ing particle swarm optimization (PSO), harmony search (HS), differential evolution
82 (DE) and the bat algorithm (BAT) are used to solve the non-linear and non-convex
83 Market Operator Transactive Energy (MO-TE) structure problem. It is common
84 knowledge that a simple optimization problem may not provide the level of ro-
85 bustness required for multiple H-MGs. In other words, the intricacy of tuning the
86 parameters in optimization algorithms may not give the expected results in such
87 cases. Since the proposed problem in this paper deals with a very large number
88 of combinations and a wider search space, it demands a robust heuristic algorithm.
89 The proposed optimization algorithm exploits the stochastic weight trade-off mech-
90 anism amongst previous velocity momentum, cognitive and social components us-
91 ing dynamic acceleration coefficients trade-off. This is done to maintain the balance
92 between global and local exploitation, and results in an improved search capability
93 of the algorithm. The incorporation of mechanisms to increase swarm members di-
94 versity through lethargy and freak factors could avoid swarm members from being
95 trapped in local minima, thereby alleviating premature convergence which is as-
96 sociated with the conventional optimization algorithms in problems with multiple
97 local optima.

98 A more accurate modeling of the MO-TE problem is carried out by considering

99 the uncertainty in the inputs and network interaction. Appropriate coalition forma-
 100 tion functions are incorporated in the fitness function to handle different equality
 101 and inequality constraints. The convergence and the solution quality of the pro-
 102 posed algorithms are affected by the selected acceleration coefficients; relatively
 103 high value of these components leads the particles to a local optimum, while rel-
 104 atively high values of cognitive components leads to wander of the particles over
 105 the search space. To improve the solution quality, these coefficients will be updated
 106 in a way that the cognitive component is reduced as the social component is in-
 107 creased with each iteration. The proposed optimization method has the flexibility
 108 to enhance both global and local exploration abilities. The results obtained are com-
 109 pared with one another and the outcome evaluations substantiate the applicability
 110 of the proposed optimization techniques for solving constrained electrical/thermal
 111 economic dispatch problems with non-smooth cost functions. The efficiency of the
 112 proposed algorithm is evaluated using a benchmark test-bed.

113 The contributions of this paper can be summarized as follows:

- 114 • Inclusion of neighbourhood grids for the players participating in the mar-
 115 ket pool. This model is a non-linear one capable of determining the opti-
 116 mum price bid for the power, generation and consumption resources when
 117 the players are inclined to form a coalition. For this purpose, a comprehen-
 118 sive mathematical model which can easily be generalized to other structures,
 119 is presented.
- 120 • A new formulation of the specific demand side management strategy for max-
 121 imizing the total profit of the grid under study is carried out with the load
 122 demand and market clearing prices.
- 123 • An increase in pay-off resulting from the participation of the consumers in the
 124 TE structure due to their inclination to participate in the DR program.
- 125 • Proposition of a day-ahead scheduling model for a multiple smart H-MG sys-
 126 tem with the possibility of coalition formation. The problem is formulated to
 127 minimize the sum value of the overall generation cost while satisfying various

128 constraints.

- 129 • Development of several hybrid optimization search algorithms with differen-
130 tial evolution to solve the complicated constrained optimization problems.
131 The mutation and selection operations for differential evolution algorithms
132 are also modified.

133 To verify the proposed day-ahead scheduling model and the solution technique,
134 several test H-MG systems are employed on a real test under different fault scenar-
135 ios.

136 The rest part of this paper is organized as follows:

137 Section 2 presents the structure of the proposed market while Section 3 gives
138 an overview of the structure which includes the uncertainty unit, TE unit and MCP
139 unit. The description of the power network under study, the objective function
140 formulation as well as the problem constraints are presented in Section 5. While
141 simulation results of the case study system are presented and discussed in Section 6,
142 Section 7 concludes the paper.

143 2. Market Operator Transactive Energy (MO-TE) structure

144 The exchange of information and communication among different players in-
145 volved in the MO-TE structure is shown in Figure 1. As observed in this figure, each
146 H-MG contains dispatchable generation units (DGU) (such as diesel generator) and
147 non-dispatchable units (NDU) (such as solar photovoltaic (PV) systems and wind
148 turbine (WT)), energy storage resources (ES) such as battery, non-responsive loads
149 (NRL) and responsive load demand (RLD). The RLD is a composite load which con-
150 sists of domestic and commercial types of load, and which can be fully curtailed
151 in accordance with the bilateral contracts signed by the H-MG owner/operator and
152 the customers. Due to the presence of these classes of consumers, MO-TE gives an
153 opportunity for the consumers to participate in the DR program to reduce cost.

154 As depicted in Figure 1, retailers sell electrical energy to the customers through
155 the MO-TE structure. MO-TE encourages investors and DER owners to participate

156 in the market by increasing the profit that results from forming a coalition in order
157 to share the energy generated in each H-MG. It also encourages the consumers to
158 follow the DR program.

159 **3. Implementation of the MO-TE structure**

160 A framework of an algorithm designed to increase the participation of the DERs
161 in MO-TE in order to reduce electricity price, to increase the generator's profit as
162 well as to reduce consumer's cost is presented in Figure 2. This framework is pre-
163 sented with a view to reducing the power in the equilibrium, managing the demand
164 side optimally considering the possibility of forming coalition among the generators,
165 and reducing the market clearing price. The MO-TE structure consists of three main
166 units: the Taguchi orthogonal test (TOAT) unit, the TE unit and the MCP unit. As
167 observed in Figure 2, the sunlight radiation data and the resulting generated PV
168 power, the load demand, MCP, SBP and SSP are all considered as uncertainty pa-
169 rameters for each hour. The TOAT ensures that the testing scenarios provide good
170 statistical information with a minimum number of tests, and significantly reduces
171 the number of the testing burden. TOAT has been proven to have the ability to opti-
172 mally select representative scenarios for testing all possible combinations. The MCP
173 unit is presented to calculate the MCP value during each time period in a two-way
174 tender system.

175 *3.1. TOAT unit*

176 The Taguchi orthogonal array test (TOAT) unit generates uncertainty scenarios
177 along with the related probability of occurrence which considers the weather con-
178 ditions of each NDU in the H-MG, as well as their power demands. This unit first
179 performs the computation of the probability of the scenario created by selecting an
180 orthogonal matrix for the existing uncertainties in the system and then creates n
181 values for the load demand, MCP, SBP and SSP using a normal distribution and the
182 radiation equation for the PV system.

183 TOAT approach has been used in a number of previous works. For example,
184 references [56] and [57] employed it to obtain robust solutions in the production

185 design of experimental problems. Further, the approach, with minimum number
 186 of scenarios insures that the experimental scenarios present good statistical infor-
 187 mation and reduces significantly the number of tests [58]. It has been proven that
 188 among all possible scenarios, TOAT has the capability to attain optimum result [59].
 189 Compared with Monte Carlo method, TOAT provides far fewer test scenarios and

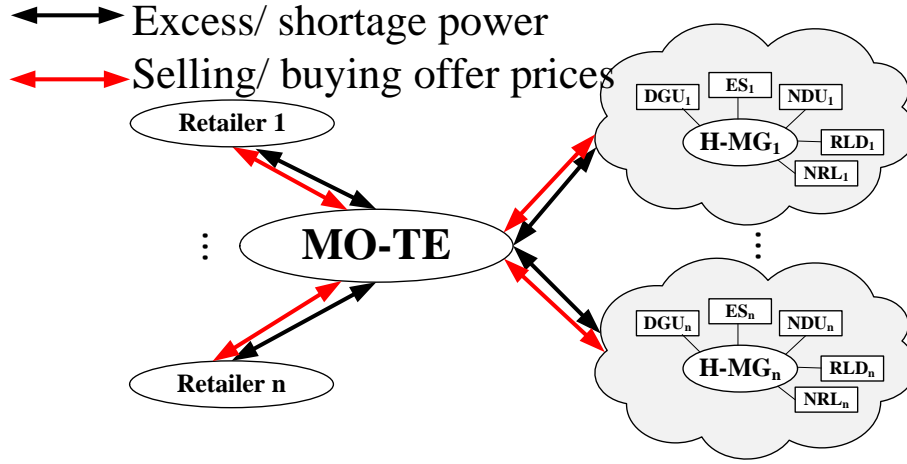


Figure 1: Exchange of information among the players in the TE structure

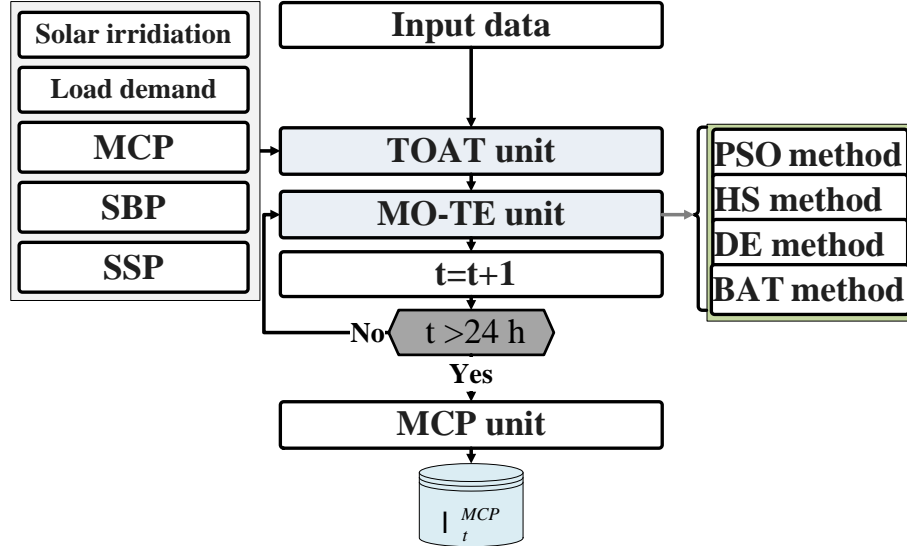


Figure 2: The proposed algorithm structure

190 leads to shorter computing time [60]. The method has be also employed in solv-
191 ing the load distribution and economic power dispatch problems in power systems
192 [61].

193 The uncertainties in the problem and their associated scenarios implemented
194 in the flowchart of Figure 3. This paper takes into account, the stochastic nature
195 of renewable energy (solar power, wind power) penetration and load demand. An
196 increase in the number of sources of uncertainty leads to an increase in the number
197 of sensitivity analyses that need to be carried out, and hence extra terms will appear
198 in the affine variables. If the uncertainty in the grid power is to be considered, then
199 the sensitivity of nodal power injections to variations grid/slack bus power injection
200 would be included in the noise terms of affine power-flow variables. However, the
201 principle remains the same.

202 In addition, constraints are set by the retailer for limiting the grid trade. These
203 constraints could be adjusted by the retailer during peak and off-peak hours, ac-
204 cording to his discretion. It indirectly represents the extent to which the upstream
205 grid can be relied on for power balance of the H-MG. In fact, the methodology does
206 consider uncertainties, since: (a) it outputs flexible rules/schedules- not specific
207 set-points for each actor of the H-MG and (b) it comes up with a merit-order dis-
208 patch list offering a fall-back, if the most profitable solution cannot be deployed.
209 The uncertainty was accounted for by the forecast for each stochastic actor of the
210 H-MG and covered by the multiple profitability levels. Further explanation regard-
211 ing this unit can be found in [33] for interested readers.

212 3.2. *TE unit*

213 Methods for implementing the Transactive energy (TE) unit, such as particle
214 swarm optimization (PSO), harmony search (HS), differential evolution (DE) and
215 the bat algorithm (BAT) have been proposed by various researchers. For example,
216 PSO is a population based evolutionary computational technique inspired by the
217 social behaviour of flocking birds, where the velocity and position of the particles
218 are updated to have additional components directed towards its own best position,
219 and the overall best position [38]. PSO makes use of stochastic weight trade-off

220 mechanism to maintain a balance between the global and local exploitation which
221 improves the search capability. The diversity of swarm members is increased by
222 using lethargy and freak factors to avoid avoid being trapped in local minima and
223 thus premature convergence. In addition, the stochastic trade-off momentum con-
224 trol factor serves to adjust the quality of a candidate solution during the late search
225 process [38].

226 The authors wish to stress that the stop criterion used in this work is not the max-
227 imum number of iterations, but rather an assessment of the information obtained
228 from splitting any of the terminal nodes of the proposed optimization algorithms
229 any further at that point. The proposed optimization algorithms do indeed replace
230 the “bad quality” solutions with the “best” ones they find, and new solutions are
231 generated using operators such as mutations and crossover. The infeasibility of in-
232 feasible solutions is determined by the unit commitment algorithm. If the unit com-
233 mitment problem with the candidate optimal operation solutions cannot be solved,
234 then new candidate values are generated. It is worth mentioning that there is no
235 loss in performance when employing the de-centralized approach, as the method-
236 ology is platform independent. The iteration process is terminated if the best objec-
237 tive value is not improved for a certain number of iterations to avoid unnecessarily
238 long iterations. To avoid premature stopping (while the objective function is still
239 evolving when the maximum number of iterations occurs), the iteration count is
240 increased until the objective value is no longer improved.

241 Figure 4 shows the flowchart for the TE unit. Each algorithm, which comprises
242 electrical and thermal parts for the initial values of the variables as presented in Fig-
243 ures 4(a)- 4(c). As observed from Figure 4(a), should there be a power shortage in
244 the electrical section, the CHP quickly swings into action to satisfy part of electrical
245 power demand. In the event that the system suffers from further power shortage,
246 then, there is the possibility of discharging the ES. It is worth mentioning that as the
247 modelling of the ES and TES is very complex due to its specific nature, the authors
248 have decided to solve it using four heuristic methods. The reason for this is to carry
249 out a comparative analysis of the results from each one. The information system for
250 the on-line dispatch can be prepared before obtaining the measured data. That is,

251 the optimal power dispatch set points for all possible reserve requirements (corre-
252 sponding to all possible uncertainties) can be made available in the database. This
253 data which corresponds to the actual measured data (uncertainty/discrepancy) is
254 selected and communicated to the local controllers in the second stage. In case
255 the possibility of supplying part of the electrical charge demand does not exist, the
256 unsupplied load demand is checked and shifted to another time period in which
257 the value of MCP is much lower. Finally, if there is a power shortage, it is mostly
258 compensated for by buying power through the retailers.

259 At some period, the excess generated electrical power is available in the H-MG
260 under the conditions that the DR constraints are determined at the beginning of
261 DR load demand; the ES is therefore exploited in charging mode. In case there is
262 a shortage of thermal power, first the H-MG is brought into service and, if TES has
263 the capability to discharge, it is discharged; otherwise it is bought from other H-
264 MGs. However, if during each time interval, excess thermal power is available for
265 each H-MG, TES is exploited in the charging mode while excess power generation
266 continues. The excess power is expended to supply a part of thermal power required
267 by the other H-MGs.

268 The proposed algorithm does not necessarily use the lower, mean and upper
269 values of each input variables. The lower and upper bounds are used to limit the
270 decision variables to reasonable values. The algorithms each generate a set of candi-
271 date solutions, each containing a sizing value for each component. Each candidate
272 solution is then evaluated using a fitness function, where the fitness is determined
273 by a unit commitment based on mixed-integer linear programming that returns the
274 operation cost. New solutions are generated by the proposed algorithms (based on
275 the previous solutions, as for classical algorithms) until one of the stopping criteria
276 is met. At the end of the process, the best solution is returned by the algorithm.
277 This solution is the set of component sizes that returns the lowest total operation
278 costs.

279 3.3. The MCP unit

280 In the electricity market, the generated/ consumed power of each generation
281 and consumption resource and their proposed price are declared to the market op-
282 erator. The energy generated in form of a stepwise function is sorted in ascending
283 order while the amount of energy consumed is sorted in the shape of descending
284 order. In this unit, as with the generators and consumers, the retailers also declare
285 their offer price to buy and sell power. The final value of MCP is determined for
286 the objective functions of each one of the market players in this unit. MCP will be
287 the interaction between consumption and generation curves. Further explanations
288 regarding this unit is presented by the authors in [33].

289 4. The advantages and disadvantages of each implemented optimization method

290 In this section, the advantages and disadvantages of each of the optimization
291 methods implemented in this study are examined briefly.

292 • PSO Method [62–64]

293 – Advantages

- 294 * It has no overlapping and mutation calculation.
- 295 * It is a zero order method which does not require complex mathe-
296 matical operations such as taking partial derivatives.
- 297 * Its rate of convergence is fast.
- 298 * In contrast to other optimization methods, none of the particles (re-
299 sponses) are eliminated and only the value of each particle changes.
- 300 * The elements have memory and each element maintains the effect
301 of the best previous position.
- 302 * It has a few parameters to handle.

303 – Disadvantages

- 304 * The efficiency of the algorithm reduces with increase in dimension
- 305 * The method easily suffers from the partial optimism.

306 * It requires more memory and this may cause it to slow down.

307 * It cannot work out the problems of non-coordinate system.

308 • **DE Method** [65–67]

309 – **Advantages**

310 * It is capable of finding the true global minimum of a multimodal

311 search space regardless of the initial parameter values.

312 * It has fewer control parameters which makes it very powerful.

313 * It is very easy to use.

314 * Fast convergence.

315 – **Disadvantages**

316 * It is easy to drop into regional optimum.

317 * It requires great ability to determine the optimal scale coefficient in

318 order to reduce the search time.

319 * Unstable convergence in the last period.

320 • **HS Method** [68, 69]

321 – **Advantages**

322 * In the genetic algorithm two chromosomes are used to generate a

323 new chromosome or solution vector. In HS method all the exiting

324 solution vectors are used in the memory to improvise new solution.

325 * Its rate of convergence is fast.

326 * It shows exceptional problem-solving ability.

327 – **Disadvantages**

328 * It can fall into local optima.

329 * It is not efficient enough for solving large-scale problems, which has

330 a slow convergence speed and low-precision solution [70].

331 • **BAT method** [71, 72]

- 332 **– Advantages**
- 333 * it is much superior to other algorithms in terms of accuracy and
- 334 efficiency [71].
- 335 * It is relatively straightforward to implement in any programming
- 336 language.
- 337 * It can provide very quick convergence at a very initial stage by
- 338 switching from exploration to exploitation.
- 339 * It has flexible control parameters.
- 340 **– Disadvantage**
- 341 * Implementation is more complicated than many other meta-heuristic
- 342 algorithms [22]
- 343 * It can fall in local optima.
- 344 * it may lead to stagnation after some initial stage.

345 **5. Problem formulation**

346 The schematic of the grid under study is shown in Figure 5. The grid has n

347 H-MGs of which the electrical and thermal DERs installed in them as well as their

348 consumers are similar. In each one of the H-MGs, there exists the electrical and

349 thermal stores and a set of generation resources such as GB, TSP, ESP, CHP as well

350 as consumers comprising NRL and RLD. In this section, the problem formulation

351 using the key components in the market structure based on Transactive Energy is

352 presented. This framework is easily expandable for other electricity distribution

353 systems with high levels of consumer participation.

354 **5.1. Objective functions of the participants in MO-TE**

355 The objective function based on maximization of the generator and retailers'

356 profits as well as the minimization of the consumers costs are formulated in Eq. 1,

357 Eq. 2 and Eq. 3, respectively. The objective functions are non-linear in nature which

can be solved for near global optima using four different heuristically guided algorithms. The effect of the large number of combinations of uncertainties on the computational speed does not matter since the first stage is for planning.

$$\max \sum_{\forall t} \sum_{\forall i} \sum_{\forall j} \sum_{\forall k} (\mathbb{R}_{t,e}^{k,i} + \mathbb{R}_{t,e}^{ES-,i} + \mathbb{R}_{t,h}^{j,i} + \mathbb{R}_{t,h}^{TES-,i} - \mathbb{C}_{t,h}^{j,i} - \mathbb{C}_{t,h}^{TES+,i} - \mathbb{C}_{t,e}^{ES+,i} - \mathbb{C}_{t,e}^{k,i}) \times \Delta t \quad (1)$$

$$\max \sum_{\forall t} \sum_{\forall i} (\mathbb{R}_{t,e}^{\text{Ret},i} - \mathbb{C}_{t,h}^{\text{Ret},i}) \times \Delta t \quad (2)$$

$$\min \sum_{\forall t} \sum_{\forall i} \sum_{\forall l} \sum_{\forall m} (\mathbb{C}_{t,h}^{p,i} + \mathbb{C}_{t,e}^{m,i}) \times \Delta t \quad (3)$$

where $\mathbb{R}_{t,e}^{k,i}$ and $\mathbb{R}_{t,h}^{j,i}$ are respectively the electrical and thermal revenue resulting from DERs k and j in H-MG i . $\mathbb{R}_{t,e}^{ES-,i}$ and $\mathbb{R}_{t,h}^{TES-,i}$ are respectively the revenue resulting from the ES and TES electrical and thermal discharge related to H-MG i at time t .

Also, $\mathbb{R}_{t,e}^{\text{Ret},i}$ and $\mathbb{R}_{t,e}^{\text{Ret}+,i}$ are respectively the revenue/ cost resulting from selling/ buying electrical power from/ to retailer H-MG i . $\mathbb{C}_{t,h}^{p,i}$ and $\mathbb{C}_{t,e}^{m,i}$ are respectively electricity costs related to p and m consumers at H-MG i .

5.2. Technical and economic constraints

5.2.1. Total electrical and thermal equilibrium

Deterministic constraints are imposed on the available and forecasted data of each DER unit, which are considered as inputs to the proposed technique. Furthermore, the inductive character of the rules of the proposed algorithm allows for flexibility when some probabilistic constraints (due to RES stochasticity) are reached. There is no need to train the system from actual data, which is one of the merits of the proposed optimization tool, provided that the forecasts and estimations for the data are realistic enough. The authors' previous work, which focused specifically on the tool ([34, 39, 73]) has clearly addressed this concern.

$$\begin{aligned} & \sum_{\forall i} \sum_{\forall k} (P_{t,e}^{k,i} + P_{t,e}^{ES-,i} + (1 - X_t^{\text{Ret}}) \cdot P_{t,e}^{\text{Ret},i}) \\ &= \sum_{\forall i} \sum_{\forall m} (P_{t,e}^{m,i} + P_{t,e}^{ES+,i} + X_t^{\text{Ret}} \cdot P_{t,e}^{\text{Ret}+,i}) \end{aligned} \quad (4)$$

$$\sum_{\forall i} \sum_{\forall j} (P_{t,h}^{j,i} + P_{t,h}^{TES-,i}) = \sum_{\forall i} \sum_{\forall l} (P_{t,h}^{p,i} + P_{t,h}^{TES+,i}) \quad (5)$$

382 Eqs. (4) and (5) state that the total power generated by electrical/ thermal
 383 generators during each time interval, must be equal to the total demand of the
 384 electrical/ thermal consumers.

385 5.2.2. Retailer constraints

386 Eq. (6) shows the cost resulting from buying electrical power from the retailer
 387 into the H-MG i while Eq. (7) presents the retailer's offer price range for buying
 388 power into the H-MG i.

$$390 \quad \mathbb{C}_{t,e}^{\text{Ret},i} = \pi_{t,e}^{\text{Ret},i} \times P_{t,e}^{\text{Ret},i} \quad (6)$$

$$0 \leq \pi_{t,e}^{\text{Ret},i} \leq \lambda_t^{\text{SBP}} \quad (7)$$

391 Also presented in Eq. (8) is the revenue resulting from selling electrical power
 392 from the H-MG i to the retailer, whereas Eq. (9) shows the price bid range for sales
 393 of power by the retailer to H-MG i.

$$395 \quad \mathbb{R}_{t,e}^{\text{Ret},i} = \pi_t^{\text{Ret},i} \times P_{t,e}^{\text{Ret},i} \quad (8)$$

$$0 \leq \pi_t^{\text{Ret},i} \leq \lambda_{t,e}^{\text{SSP}} \quad (9)$$

396 Eqs. (10) and (11) show the exchanged power constraints between H-MG i and
 398 retailer.

$$399 \quad P_{t,e}^{\text{Ret},i} \leq X_t^{\text{Ret}} \times \bar{P}^{\text{Ret}} \quad (10)$$

$$400 \quad P_{t,e}^{\text{Ret},i} \leq (1 - X_t^{\text{Ret}}) \times \bar{P}^{\text{Ret}} \quad (11)$$

$$\bar{P}^{\text{Ret}} \leq (P_{t,e}^{\text{ESP},i} + P_{t,e}^{\text{CHP},i} + P_{t,e}^{\text{ES},i}) \quad (12)$$

401 5.2.3. H-MG i constraints

402 ES and TES constraints in H-MG i

$$403 \quad \mathbb{C}_{t,e}^{\text{ES},i} = \pi_{t,e}^{\text{ES},i} \times P_{t,e}^{\text{ES},i} \quad (13)$$

$$404 \quad 0 \leq \pi_{t,e}^{\text{ES},i} \leq \lambda_{t,e}^{\text{MCP}} \quad (14)$$

$$405 \quad \mathbb{R}_{t,e}^{\text{ES},i} = \pi_t^{\text{ES},i} \times P_{t,e}^{\text{ES},i} \quad (15)$$

$$406 \quad 0 \leq \pi_t^{\text{ES},i} \leq \lambda_{t,e}^{\text{MCP}} \quad (16)$$

where $C_{t,e}^{ES+,i}$, $R_{t,e}^{ES-,i}$, $\pi_{t,e}^{ES+,i}$ and $\pi_{t,e}^{ES-,i}$ respectively show the cost, revenue, and price bid resulting from buying/ selling electrical power by ES in H-MG i. Eqs. (17) to (19) present ES maximum and minimum charge/ discharge in H-MG i.

$$\underline{E}^{ES,i} \leq E_{t,e}^{ES,i} \leq \bar{E}^{ES,i} \quad (17)$$

$$P_{t,e}^{ES-,i} \leq \bar{P}^{ES-,i} \times X_t^{ES,i}, \quad P_{t,e}^{ES-,i} \geq 0 \quad (18)$$

$$P_{t,e}^{ES+,i} \leq \bar{P}^{ES+,i} \times X_t^{ES,i}, \quad P_{t,e}^{ES+,i} \geq 0 \quad (19)$$

Eqs. (20) and (21) are the charge/ discharge maximum limits for the energy in Eq. (22).

$$P_{t,e}^{ES-,i} \times \Delta t \leq (E_{t-1}^{ES,i} - \underline{E}^{ES,i}) \quad (20)$$

$$P_{t,e}^{ES+,i} \times \Delta t \leq (\bar{E}^{ES,i} - E_{t-1}^{ES,i}) \quad (21)$$

$$E_{t,e}^{ES,i} = E_{t-1,e}^{ES,i} + (P_{t-1}^{ES+,i} - P_{t-1}^{ES-,i}) \times \Delta t \quad (22)$$

Eq. (23) depicts the cost resulting from buying thermal power by TES in the charging mode while Eq. (24) is the price bid interval for buying thermal power by TES.

$$C_{t,h}^{TES+,i} = \pi_{t,h}^{TES+,i} \times P_{t,h}^{TES+,i} \quad (23)$$

$$0 \leq \pi_{t,e}^{TES+,i} \leq \max(\pi_{t,h}^{HHW,i}, \pi_{t,h}^{TD,i}) \quad (24)$$

$R_{t,h}^{TES-,i}$ in Eq. (25) is the revenue resulting from sales of thermal power generated by TES in the discharging mode and $\pi_{t,h}^{TES-,i}$ in Eq. (26) is the price bid variations range for selling thermal power by TES.

$$R_{t,h}^{TES-,i} = \pi_{t,h}^{TES-,i} \times P_{t,h}^{TES-,i} \quad (25)$$

$$0 \leq \pi_{t,h}^{TES-,i} \leq \min(\max(\pi_{t,h}^{CHP,i}, \pi_{t,h}^{GB,i}), \pi_{t,h}^{TSP,i}) \quad (26)$$

In Eqs. (27) to (29), TES maximum and minimum charge/ discharge limitations are shown.

$$\underline{E}^{TES,i} \leq E_{t,h}^{TES,i} \leq \bar{E}^{TES,i} \quad (27)$$

$$P_{t,h}^{TES-,i} \leq \bar{P}^{TES-,i} \times X_t^{TES,i}, \quad P_{t,h}^{TES-,i} \geq 0 \quad (28)$$

$$P_{t,h}^{TES+,i} \leq \bar{P}^{TES+,i}, \quad P_{t,h}^{TES+,i} \geq 0 \quad (29)$$

433 Eqs. (30) and (31) show the discharge/ charge maximum limits for the energy
434 in TES while Eq. (32) presents the energy equilibrium in TES.

$$435 \quad P_{t,h}^{\text{TES},i} \times \Delta t \leq (E_{t-1}^{\text{TES},i} - \underline{E}^{\text{TES},i}) \quad (30)$$

$$436 \quad P_{t,h}^{\text{TES}+,i} \times \Delta t \leq (\bar{E}^{\text{TES},i} - E_{t-1}^{\text{TES},i}) \quad (31)$$

$$437 \quad E_{t,h}^{\text{TES},i} = E_{t-1,h}^{\text{TES},i} + (P_{t-1,h}^{\text{TES}+,i} - P_{t-1,h}^{\text{TES},i}) \times \Delta t \quad (32)$$

438 EV constraints in H-MG i

$$439 \quad \text{if } \chi_t^{\text{EV},i} = 1 \implies \underline{P}^{\text{EV},i} \leq P_{t,e}^{\text{EV},i} \leq \bar{P}^{\text{EV},i} \quad (33)$$

440 Eq. (34) states that the $\text{SOC}_t^{\text{EV},i}$ of the automobile battery during each time
441 interval related to H-MG i, must be less than its maximum value. It should be noted
442 that Eq. (35) is the automobile battery power balance constraint. If EV is plugged
443 out or once $\text{SOC}_t^{\text{EV},i}$ is reached to $\overline{\text{SOC}}^{\text{EV},i}$, then the charging process will be finished

$$444 \quad \text{SOC}_t^{\text{EV},i} \leq \overline{\text{SOC}}^{\text{EV},i} \quad (34)$$

$$445 \quad \text{SOC}_t^{\text{EV},i} = \text{SOC}_{t-1}^{\text{EV},i} - \frac{P_{t,e}^{\text{EV}+,i} \times \chi_t^{\text{EV},i} \times \Delta t}{E_{\text{Tot}}^{\text{EV},i}} \quad (35)$$

$$446 \quad \text{if } \chi_t^{\text{EV},i} = 0 \ \& \ \text{SOC}_t^{\text{EV},i} = \overline{\text{SOC}}^{\text{EV},i} \implies P_{t,e}^{\text{EV},i} = 0 \quad (36)$$

447 Eq. (37) is the cost of buying electrical power while Eq. (38) presents the offer
448 price range for buying power by EV.

$$449 \quad C_{t,e}^{\text{EV}+,i} = \pi_{t,e}^{\text{EV}+,i} \times P_{t,e}^{\text{EV}+,i} \quad (37)$$

$$450 \quad 0 \leq \pi_{t,e}^{\text{EV}+,i} \leq \lambda_{t,e}^{\text{MCP}} \quad (38)$$

451 ESP constraints in H-MG i

452 The ESP generated power limitation is as shown in Eq. (39).

$$453 \quad \underline{P}^{\text{ESP},i} \leq P_{t,e}^{\text{ESP},i} \leq \overline{\text{ESP}},i \quad (39)$$

454 Eq. (40) shows the revenue resulting from generating electrical power by ESP
455 whereas Eq. (41) shows the price bid range for selling power by ESP.

$$456 \quad R_{t,e}^{\text{ESP},i} = \pi_{t,e}^{\text{ESP},i} \times P_{t,e}^{\text{ESP},i} \quad (40)$$

$$457 \quad 0 \leq \pi_{t,e}^{\text{ESP},i} \leq \lambda_{t,e}^{\text{MCP},i} \quad (41)$$

458 TSP constraints in H-MG i

Eq. (42) shows the generated thermal power income of TSP, and Eq. (43) shows the range of price bid for selling power by TSP.

$$\mathbb{R}_{t,h}^{\text{TSP},i} = \pi_{t,h}^{\text{TSP},i} \times P_{t,h}^{\text{TSP},i} \quad (42)$$

$$0 \leq \pi_{t,h}^{\text{TSP},i} \leq (\pi_{t,e}^{\text{TES},i}, \pi_{t,h}^{\text{CHP},i}, \pi_{t,h}^{\text{GB},i},) \quad (43)$$

CHP constraints in H-MG i

Eqs. (44)-(46) presents the power generation limitation for the CHP; where $\text{FU}_t^{\text{CHP},i}$, $\zeta_{e1}^{\text{CHP},i}$ and $\zeta_h^{\text{CHP},i}$ are respectively the fuel, electrical efficiency and thermal efficiency of the CHP.

$$\underline{P}^{\text{CHP},i} \leq P_{t,e}^{\text{CHP},i} \leq \bar{P}^{\text{CHP},i} \quad (44)$$

$$P_{t,e}^{\text{CHP},i} = \text{FU}_t^{\text{CHP},i} \times \zeta_{e1}^{\text{CHP},i} + \zeta_{e2}^{\text{CHP},i} \quad (45)$$

$$P_{t,e}^{\text{CHP},i} = \zeta_{e1}^{\text{CHP},i} \times \frac{P_{t,h}^{\text{CHP},i}}{\zeta_h^{\text{CHP},i}} + \zeta_{e2}^{\text{CHP},i} \quad (46)$$

Eq. (47) is the cost resulting from power generation using CHP. Eq. (48) shows the price bid range for generating power by CHP. Also, Eqs. (49) and (50) state the revenue resulting from selling electrical and thermal powers generated using the CHP.

$$\mathbb{C}_t^{\text{CHP},i} = \pi_t^{\text{NG}} \times \text{FU}_t^{\text{CHP},i} \quad (47)$$

$$\mathbb{C}_t^{\text{CHP},i} \leq \pi_t^{\text{CHP},i} \leq 2 \times \mathbb{C}_t^{\text{CHP},i} \quad (48)$$

$$\mathbb{R}_{t,e}^{\text{CHP},i} = \pi_{t,e}^{\text{CHP},i} \times P_{t,e}^{\text{CHP},i} \quad (49)$$

$$\mathbb{R}_{t,h}^{\text{CHP},i} = \pi_{t,h}^{\text{CHP},i} \times P_{t,h}^{\text{CHP},i} \quad (50)$$

GB constraints in H-MG i

The limit of the power generated by GB is shown in Eq. (51).

$$0 \leq P_{t,h}^{\text{GB},i} \leq \bar{P}_{t,h}^{\text{GB},i} \quad (51)$$

Eq. (52) shows the cost resulting from generating thermal power by GB while Eq. (53) presents the amount of fuel consumed using GB and Eq. (54) shows the price bid range for selling power through GB.

$$\mathbb{C}_{t,h}^{\text{GB},i} = \pi_{t,h}^{\text{NG}} \times \text{FU}_t^{\text{GB},i} \quad (52)$$

$$\text{FU}_t^{\text{GB},i} = \frac{P_t^{\text{GB},i}}{\zeta_h^{\text{GB}}} \quad (53)$$

$$\mathbb{C}_{t,h}^{\text{GB},i} \leq \pi_{t,h}^{\text{GB},i} \leq 2 \times \mathbb{C}_{t,h}^{\text{GB},i} \quad (54)$$

The revenue resulting from selling thermal power by GB is shown in Eq. (55).

$$\mathbb{R}_{t,h}^{\text{GB},i} = \pi_{t,h}^{\text{GB},i} \times P_{t,h}^{\text{GB},i} \quad (55)$$

5.2.4. Consumer constraints

DR constraints

Eq. (56) shows that the value of shiftable power must be less than or equal to the difference of the total consumed power and the total generated power. Eq. (58) and Eq. (59) show that the DR limit between two consecutive intervals must not exceed a certain limit.

$$P_t^{\text{DR},i} \leq (P_t^{\text{TCP},i} - P_t^{\text{TGP},i}) \cdot X_t^{\text{DR},i} \quad (56)$$

$$P_t^{\text{DR}+,i} \leq (P_t^{\text{TGP},i} - P_t^{\text{TCP},i}) \cdot (1 - X_t^{\text{DR},i}) \quad (57)$$

$$P_t^{\text{DR}+,i} \leq k_e \times P_t^{\text{NRL},i} \times (1 - X_t^{\text{DR},i}) \quad (58)$$

$$-k_t \leq (P_t^{\text{DR}+,i} - P_{t-1}^{\text{DR}+,i}) \leq k_t \quad (59)$$

ATL and AEL constraints

Eqs. (60) and (61) are the costs resulting from buying electric and thermal power by AEL and ATL. Also, Eqs. (62) and (63) present the price bid interval for buying power by AEL and ATL.

$$\mathbb{C}_{t,e}^{\text{AEL},i} = \pi_{t,e}^{\text{AEL},i} \times P_{t,e}^{\text{AEL},i} \quad (60)$$

$$\mathbb{C}_{t,e}^{\text{ATL},i} = \pi_{t,e}^{\text{ATL},i} \times P_{t,e}^{\text{ATL},i} \quad (61)$$

$$\lambda_{t,e}^{\text{MCP}} \leq \pi_{t,e}^{\text{AEL},i} \leq 2 \times \lambda_{t,e}^{\text{MCP}} \quad (62)$$

$$\max(\pi_{t,h}^{\text{TES},i}, \pi_{t,h}^{\text{CHP},i}, \pi_{t,h}^{\text{GB},i}, \pi_{t,h}^{\text{TSP},i}) \leq \pi_{t,h}^{\text{ATL},i} \leq 2 \times \max(\pi_{t,h}^{\text{TES},i}, \pi_{t,h}^{\text{CHP},i}, \pi_{t,h}^{\text{GB},i}, \pi_{t,h}^{\text{TSP},i}) \quad (63)$$

TD constraints

Eq. (64) is the cost of buying thermal power by TD while Eq. (65) states the offer price range for buying power by TD.

$$\mathbb{C}_{t,h}^{\text{TD},i} = \pi_{t,h}^{\text{TD},i} \times P_{t,h}^{\text{TD},i} \quad (64)$$

$$0 \leq \pi_{t,h}^{\text{TD},i} \leq \min(\pi_{t,h}^{\text{TES},i}, \pi_{t,h}^{\text{CHP},i}, \pi_{t,h}^{\text{GB},i}, \pi_{t,h}^{\text{TSP},i}) \quad (65)$$

512 REF constraints

513 Eqs. (66)-(70) state the modeling of REF. $\mathbb{C}_{t,e}^{\text{REF},i}$ is the cost resulting from buying
 514 power by REF and $\pi_{t,e}^{\text{REF},i}$ represent the offer price interval for buying power.

$$\begin{cases} \text{if } \underline{T}^{\text{REF},i} \leq T_t^{\text{RET}} \leq \bar{T}^{\text{REF},i} & X_t^{\text{REF},i} = 1 \\ \text{Otherwise} & X_t^{\text{REF},i} = 0 \end{cases} \quad (66)$$

$$516 X_t^{\text{REF},i} = 1 \implies P_{t,e}^{\text{REF},i} = \bar{P}^{\text{REF},i} \quad \& \quad T_t^{\text{REF},i} = T_{t-1}^{\text{REF},i} - T^{\text{RED},i} \quad (67)$$

$$517 X_t^{\text{REF},i} = 0 \implies P_{t,e}^{\text{REF},i} = 0 \quad \& \quad T_t^{\text{REF},i} = T_{t-1}^{\text{REF},i} + T^{\text{RED},i} \quad (68)$$

$$518 \mathbb{C}_{t,e}^{\text{REF},i} = \pi_{t,e}^{\text{REF},i} \times P_{t,e}^{\text{REF},i} \quad (69)$$

$$519 0 \leq \pi_{t,e}^{\text{REF},i} \leq \lambda_{t,e}^{\text{MCP}} \quad (70)$$

520 DW constraints

521 The modeling of DW are presented in Eqs. (71)-(74). Eqs. (73) and (74) respec-
 522 tively show the cost resulting from buying power by DW and the price bid interval
 523 for buying power.

$$524 \text{if } X_t^{\text{DW},i} = 1 \implies P_{t,e}^{\text{DW},i} = \bar{P}^{\text{DW},i}, \quad DT_t^{\text{DW},i} = DT_{t-1}^{\text{DW},i} + 1 \quad (71)$$

$$525 \text{if } DT_t^{\text{DW},i} = \bar{DT}^{\text{DW},i} \implies P_{t,e}^{\text{DW},i} = 0, \quad X_t^{\text{DW},i} \quad (72)$$

$$526 \mathbb{C}_{t,e}^{\text{DW},i} = \pi_{t,e}^{\text{DW},i} \times P_{t,e}^{\text{DW},i} \quad (73)$$

$$527 0 \leq \pi_{t,e}^{\text{DW},i} \leq \lambda_{t,e}^{\text{MCP}} \quad (74)$$

528 HHW constraints

529 The modeling of HHW are presented in Eqs. (75)-(79).

$$\begin{cases} \text{if } \underline{T}^{\text{HHW},i} \leq T_t^{\text{HHW}} \leq \bar{T}^{\text{HHW},i} & X_t^{\text{HHW},i} = 0 \\ \text{Otherwise} & X_t^{\text{HHW},i} = 1 \end{cases} \quad (75)$$

$$531 X_t^{\text{HHW},i} = 1 \implies \begin{cases} P_{t,e}^{\text{HHW},i} = \bar{P}^{\text{HHW},i} \\ T_t^{\text{HHW},i} = T_{t-1}^{\text{HHW},i} + T^{\text{INC},i} \end{cases} \quad (76)$$

$$532 X_t^{\text{HHW},i} = 0 \implies \begin{cases} P_{t,e}^{\text{HHW},i} = 0 \\ T_t^{\text{HHW},i} = T_{t-1}^{\text{HHW},i} - T^{\text{INC},i} \end{cases} \quad (77)$$

$$C_{t,h}^{HHW,i} = \pi_{t,h}^{HHW,i} \times p_{t,h}^{HHW,i} \quad (78)$$

$$0 \leq \pi_{t,h}^{HHW,i} \leq \max(\pi_{t,h}^{TES,i}, \pi_{t,h}^{CHP,i}, \pi_{t,h}^{GB,i}, \pi_{t,h}^{TSP,i},) \quad (79)$$

5.3. Mathematical modelling of PV, WT and load demand uncertainty

Since the market is based on predicted data and generation units are variable, uncertainty must be considered. In order that the predicted data mimics reality, probabilistic models are used.

5.3.1. Modelling of load demand uncertainty

Load uncertainty can be modelled using a normal distribution curve. The mean value in the load normal curve distribution is equal to the predicted load for each time interval. The standard deviation is obtained from the load prediction method based on experience and previous electricity consumption patterns. To simplify our analysis, the normal distribution can be divided into several sections showing the load occurrence probability with the value equal to the mean value of that section. In this study the normal probability distribution curve shown in Figure 6 is used [74, 75].

5.3.2. WT uncertainty modelling

Bearing in mind that wind supply is stochastic in nature, the calculation of wind speed variability was carried out using the Weibull distribution. The mean value of this distribution is the wind speed prediction datum. The Weibull distribution curve can also be divided into several separate sections. The possibility of occurrence of each interval is determined from the corresponding wind speed and the mode of each section. The wind speed probability distribution curve in this study is divided in the five pieces distribution density function as shown in Figure 7 [76, 77].

Wind output power is determined from the power function based on wind speed according to the following relation.

$$P_t^{WT}(v) = \begin{cases} (\frac{P_r}{V_r - V_{ci}})(v - V_{ci}) & \text{if } V_{ci} \leq v \leq V_r \\ P_r & \text{if } V_r \leq v \leq V_{co} \\ 0 & \text{others} \end{cases} \quad (80)$$

where $P_t^{WT}(v)$ is total wind power output at wind speed v , v is the wind speed, P_r is total rated power of wind turbines, V_r is the rated wind speed and V_{ci} turbine cut-in wind speed and V_{co} is the cut-out wind speed. If the turbine generation starts at the speed V_{ci} ; the output power will increase proportionally to speed increase from V_{ci} to V_r and the nominal power P_r is generated when the wind speed is varied between V_r and V_{co} . For security reasons, the turbine will turn off at speed V_{co} and the output power will be zero at a speed outside the mentioned limits.

5.3.3. Modelling of uncertainty in PV system

The amount of solar radiation that reaches the earth, in addition to the external daily and annual rotation of the sun, depends on the geographical position (length, width and height) and climatic conditions (for example cloud cover). The PV output power is dependent on the amount of solar radiation on the PV panel surface. The hourly distribution for solar radiation can be divided into five sections similar to the Weibull distribution model for wind speed, as illustrated in Figure 8 [78]. PV system power distribution is obtained based on the radiation distribution. The PV system output power is calculated as follows:

$$P_t^{PV} = A_C \cdot \eta \cdot I_t^\beta \quad (81)$$

where A_C is the area of array surface [m^2], I_t^β is the amount of solar radiation over a surface with β slope to the horizon surface [kWm^{-2}], η is the efficiency of PV system at the realistic reporting conditions.

6. Results and discussion

In this section, the results of simulation of the four methods are presented and discussed. The grid under study has three H-MGs called A, B and C which include

580 different DER and consuming resources. The specifications of these resources are
581 listed in the appendix. A fault on a H-MG will cause serious consequences to the sys-
582 tem and customers' equipment. It requires not only concentrated attention to avoid
583 the fault but also recovery measures to reduce the impact once the fault has oc-
584 curred. Constructing a re-configurable scheme for different fault modes will greatly
585 reduce losses and inconvenience. Hence, the proposed optimization algorithm is
586 employed to solve the optimal day-ahead scheduling problem under different fault
587 scenarios, to help verify the robustness of the algorithm.

588 The proposed methodologies provide a number of possible dispatch combina-
589 tions. Hence, there is a large number of fallback positions that the optimization
590 algorithm can revert to in the case of any imbalance. When an intra-period im-
591 balance occurs, the next most suitable dispatch is applied immediately. A 1-hour
592 resolution rolling-horizon simulation is used to verify the validity of the obtained
593 scheduling solutions. It also helps to adjust the operation scheduling values if re-
594 quired, especially as the proposed optimization algorithm input data use a 1-day
595 resolution to improve computation speed. Simulations were carried out on an Intel
596 (R) CoreTM: 5-3320M CPU @2.6GHz computer with 4:00GB RAM. The MATLAB
597 software was used to solve the optimization problems.

598 It is worth mentioning that there are no infeasible dispatches in the problem.
599 A solution/dispatch is considered infeasible if it cannot be realized in real time.
600 The proposed optimization methodologies will produce a number of profitable dis-
601 patches at various profitability levels when it is executed in the hour-ahead horizon.
602 However, in real time, it is possible that due to considerable deviations from the
603 forecast, the schedule of the highest profitability may prove to be infeasible; hence
604 the next best profitable schedule will be applied. This method outperforms previous
605 approaches specifically in terms of outputting flexible schedules that cater for the
606 mitigation of deviations of a H-MG. It also takes into account the risk of infeasible
607 solutions through a merit order list of alternative dispatches.

608 The values of all the powers generated by electrical and thermal DERs in each
609 H-MG as well as the total value of electrical powers sold/ bought to/ from H-MGs
610 from/ to retailer are shown in Figure 9. As observed in Figure 9(a), the maximum

power generated by the electrical DERs in H-MG #A is obtained by the HS method. This is why no power is sold from this H-MG to the retailer. For any uncertainty less than or equal to the maximum uncertainty, the corresponding reserve can be directly fetched from the uncertainty versus reserve information. This reduces the computational time of dynamic dispatch to approximately zero (around 0.1ms) due to the absence of recalculation of optimal power-flow for the measured data. The execution time will be the time taken for data selection, fetching and communication only.

In the proposed method, the sum of the power allocated to DR+ has the least value relative to other methods. The reason for the increase in the amount of generated power in this H-MG is to allow it to sell the generated power to other H-MGs. In this manner, the amount of H-MG #A revenue increases. As for H-MG #B, the conditions are completely different because the power generated using the DE method is higher than that for other methods. The reason for this is basically due to the power purchased from the retailer.

Overall, by comparing Figure 9(b) and 9(c), it is observed that H-MG #B in the PSO optimization method has a better interaction with the retailer compared to other methods. Bearing in mind that the average value of electrical MCP using the PSO method is lower than for other methods, H-MG #B supplies the number of consumers with lower MCP using the power purchased from the retailer. Furthermore, it is worth noting that the value of the DR+ power sum using this method is 27% of the total consumed DR+ power using other optimization methods. This means that in the MO-TE structure, the HS method attempts to buy more power from the retailer in order to supply more RLD loads. As observed in Figure 9(a) in H-MG #C the value of total power generated using the BAT method is highest compared to other optimization methods.

Similarly, from Figures 9(b) and 9(c), the power exchange value of the H-MG with the retailer has its highest limit in this method. The main reason for this is that the value of sum DR- has reached its lowest possible limit compared to other methods which is only 6%. On the other hand, about 26% of the total DR+ power was obtained with the BAT method. This figure is very significant when compared

642 to the other methods. Knowing that the average value of electrical MCP in the BAT
643 method is lower than the HS and DE methods, provides positive opportunities for
644 supplying the consumers of this H-MG at lower price.

645 The total power generated by the thermal DER for each H-MG is shown in Fig-
646 ure 9(d). As observed in H-MGs #A and #C, the highest thermal power is generated
647 by the HS method, whereas H-MG #B power is generated using the BAT method. In
648 essence, the average value of thermal MCP using HS and BAT methods is lower than
649 those for other methods. This information is very important to select further power
650 generation by thermal DER resources. In other words, while the minimum value
651 of thermal MCP is obtained in these methods, the maximum value of thermal MCP
652 is obtained in the DE and PSO methods which could lead to a significant increase
653 in the value of thermal power cost generated by these methods. As a result, less
654 thermal power generated by the DE and PSO methods leads to a profit increase for
655 the H-MG owner. Meanwhile the consumer that required maximum total thermal
656 power has also been fulfilled.

657 Figure 10 presents the consumed load demand profile in each H-MG. It can be
658 seen Figure 10(a) that the consumption peak value using the PSO and BAT methods
659 in H-MG #A was shifted to non-peak intervals. Using the fact that the average MCP
660 value during peak intervals is high in all the implemented optimization methods,
661 then the participation of consumers in DR program incurs more expenses to H-MGs
662 owners and/ or retailers in exchange for the supply of its required power. However,
663 the total value of DR+ in the BAT method is about 28% of the total value of DR+, it
664 is expected that the PSO method follows a similar pattern regarding participation
665 of consuming resources to increase the DR+ value. After evaluation, it is observed
666 that about 26% of the DR+ generation among the methods was obtained with PSO.

667 Despite this fact, it is observed that the total values of DR- in the DE and BAT
668 methods are equal to each other, which is about 28% of the total DR- proposed
669 by all the methods. The minimum value of total DR- was obtained from the HS
670 method. This shows the reluctance of this method to shift the load demand from
671 one time period with high price to another with lower price. The main reason
672 for this occurrence is that the value of electricity generation cost by the H-MGs

altogether has the highest value for all the methods. This is about a 28% reduction relative to the DE method that is providing the lowest cost of generating electricity. Using the HS method, H-MG #B has the maximum value of DR+ while DR- shows a significant reduction in its value.

As for the maximum electricity generation cost, the proposed algorithm shows a greater desire to reduce the value of the consumed load demand in the H-MG. An important point to make here is that although the electricity generation value in the BAT method was the highest after HS, the total value of DR- has become the lowest relative to other methods. For this reason, the BAT method has increased the DR+ value. In H-MG #C, DR+ and DR- values are maximum relative to other methods using the PSO method. The performance of this method is justified with its lowest cost of electricity after the DE method.

In H-MG #C, it is highly desirable that more DR+ be supplied using the BAT method while bringing DR- value to the minimum as was pointed out before. The electricity generation cost in the BAT method is high, as also is the average electrical MCP value compared to other methods during the 24h performance of the grid under study; by supplying the DRs at suitable times, the method therefore tries to reduce the cost paid by the consumers.

The percentage of the electrical power generated by the H-MGs for each optimization technique adopted in this study is shown in Figure 11 while that of thermal power is shown in Figure 12.

The thermal power supply required by the consumer is similar to that of electrical power. Therefore, the thermal power equilibrium for each H-MGs can be attained by implementing the optimization algorithms. Because supply of thermal power makes the thermal power GB resource to participate in each one the H-MGs. It should be noted that part of the thermal power is supplied by the GB which is brought in operation during the period 16:00-20:00. The pricing strategy by each of presented optimization methods somehow determines the suitable price offer for the GB during the period in which the CHP thermal power value is proportional to the electrical power. As a result, the thermal load requirement difference is satisfied by the GB.

704 The values of electrical and thermal MCPs obtained from simulation using each
705 of the optimization methods are shown in Figures 13(a) and 13(b), respectively. As
706 observed from Figure 13(a), all the methods for reducing electrical MCP relative to
707 thermal MCP have very good performance over the complete time period. At the
708 start of the system's daily performance, the PSO method has a better performance
709 in reducing the MCP relative to the BAT method which during this time interval has
710 the poorest performance. In the morning, the PSO method is the most successful for
711 reducing the MCP. During this time interval the worst is related to the HS method
712 for which the electrical MCP increases for about 83%.

713 HS performance over this latter time period is the worst among all the methods,
714 so much so that it has out-weighed its very good performance at the beginning of
715 the day. The PSO method in this interval obtains less MCP value relative to DE
716 with about 34% of the time during the DERs and consumers proper management.
717 Although PSO has shown the best performance during this time interval, it has the
718 worst performance in the period from afternoon to sunset. The best performance to
719 reduce MCP in this period from afternoon to sunset HS method which has obtained
720 the minimum value of electrical MCP at about 78% of the time when compared
721 with PSO.

722 During the day's last hours, the HS method imposes a higher value of MCP
723 on the consumers for 22% of the time. Altogether, the best method over the 24h
724 performance of the MO-TE structure is obtained for electrical MCP using the HS
725 method relative to the PSO method. This is about 6%, relative to BA, about 9%
726 relative to the DE method; about 62% of the time a reduced MCP is obtained. As
727 observed from Figure 13(b), at the beginning, from midnight until morning, the
728 PSO method has a significant share in reducing the value of the thermal MCP. For
729 this reason, its value is always obtained relative to other optimization methods at
730 minimum value.

731 The worst result during this time interval is related to BAT where for about 77%
732 of the time, a higher thermal MCP value results from using the PSO method. In
733 the morning, the best performance is given by DE but the PSO's performance has
734 reduced so much that there is a reduction in the thermal MCP for about 45% of

735 the time. In the time interval 12:00 to 18:00 the DE method gave the best perfor-
736 mance. In contrast to DE, BAT had a poor performance whose operation is related
737 to DE that was 70% weaker. During the last hours of the day in contrast to the
738 previous intervals, BAT had the best performance relative to others. Altogether, for
739 the powers consumed in all the H-MGs, the DE algorithm with less than 2% had
740 better performance relative to BAT, 28% better relative to HS and PSO in reducing
741 the MCP.

742 The convergence characteristic of the proposed algorithms is compared with
743 each other and depicted in Figure 14. This figure implies that the proposed algo-
744 rithm based on the DE method outperforms the other optimization techniques in
745 convergence speed; however the proposed algorithm based on BAT method achieved
746 a better performance from an optimality of objective function point of view. The
747 obtained maximum profit for DE and BAT methods are £8.5 and £9.7, with the cor-
748 responding CPU-time of 8.085s and 9.705s (as shown in Table 1), respectively. It
749 can be observed that the PSO method converges to the optimal solution in a greater
750 number of iterations. It is observed from this figure that HS has a better convergence
751 characteristic, in comparison with PSO and BAT. By comparing the convergence
752 properties of the proposed algorithms, both the speed and ability of the proposed
753 approaches to find better solutions can be observed in Figure 14. These imply the
754 capability of the proposed methods for solving such complicated economic dispatch
755 problems. The maximum iteration number for this case is set to 100 iterations.

756 In order to compare the computation, it should be mentioned that both CPU
757 speed and simulation times for all methods are provided in Table 1. Computation
758 time has a direct relation with CPU speed. Relative simulation time is calculated by
759 multiplying relative CPU speed by the reported simulation time. Although the ob-
760 tained profit by PSO is £7.9 (i.e., 22.6%) less than the profit obtained by BAT, but the
761 corresponding CPU-time is much less in comparison with the very high CPU-time
762 of BAT. The negligible reduction of profit at the expense of a significant increase
763 of CPU-time may not be desirable from the real-time operation perspective. In it
764 important to mention that in real-time applications, the optimal DER schedule is
765 needed for the next few minutes, subject to the unpredicted uncertainty param-

ters in the order of minutes (e.g., 5-min intervals). The results presented in Table 1 substantiate the fact that the proposed methods are well capable of attaining the optimal solution of offer prices and quantities in a very short time. Hence, the proposed methods are efficient for solution of economic dispatch in real-time environment.

Table 1: Comparison of the absolute and relative CPU time for test system

Method	CPU speed (GHz)	Absolute time (s)	Relative CPU time (s)
DE	3	5.39	8.085
HS	3	5.33	7.995
PSO	3	5.26	7.89
BAT	3	6.47	9.705

Table 2 show the minimum, average, maximum and standard deviation of the objective function for different numbers of trial runs. The maximum iteration number for this simulation is selected to be 100. The results justify the applicability of the proposed methods for solving the constrained economic dispatch problem with non-smooth cost functions.

Table 2: Analysis of objective function for different number of trial runs

Method	Number of runs	Minimum profit (£)	Average profit (£)	Maximum profit (£)	Standard deviation (£)
DE	50	4.87	6.16	7.5	0.98
HS		3.6	7.14	7.64	1.23
PSO		4.66	6.15	6.98	0.93
BAT		4.83	6.81	8.4	1.34
DE	100	5.87	8.16	8.5	0.78
HS		4.6	8.34	8.84	1.03
PSO		5.66	7.15	7.9	0.56
BAT		5.93	7.93	9.7	1.23

7. Conclusion

This paper has proposed an algorithm for the optimum use of the existing electrical/ thermal resources in home Microgrids. The proposed framework provided an optimum timing for power exchange among the H-MGs while satisfying the objective functions and technical constraints. Establishing a coalition among the H-MGs,

781 the method when tested, considered power balancing, demand side management,
782 market clearing price reduction and profit increase of the players in the market. The
783 optimality of the obtained results and the ability of the proposed structure to change
784 the input parameters were compared with each other using several methods. With
785 technical and economic constraints, the timing of connection of appliances and elec-
786 trical machines were included. The optimum control of ES resources and demand
787 side management led to a reduction in the exploitation cost of each H-MG which re-
788 sulted in profit increase. The proposed algorithm could be exploited to fix different
789 structures with different objective functions.

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800 Appendix

801 H-MG resources specifications and constant parameter values is listed in Table 3.

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Table 3: H-MG resources specifications and constant parameter values

Name of DER	Variable	Value	Name of DER	Variable	Value
GB	$\zeta_{h,e}^{GB}$	85%	ES	$\overline{P}_{t,e}^{ES+}$	30
	\overline{P}_h^{GB}	12		$\underline{P}_{t,e}^{ES+}$	0.34
	\underline{P}_h^{GB}	3.6		$\overline{P}_{t,e}^{ES-}$	30
				$\underline{P}_{t,e}^{ES-}$	0.34
				$\underline{P}_{t,e}^{ES-}$	0.34
				\underline{SOC}^{ES}	0
				\overline{SOC}^{ES}	100%
CHP	ζ_{e2}^{CHP}	-94.6916	EV	$\overline{P}_{t,e}^{EV+}$	3.2
	ζ_{e1}^{CHP}	0.358511		$\underline{P}_{t,e}^{EV+}$	0
	\overline{P}_e^{CHP}	8		\underline{SOC}^{EV}	0
	\underline{P}_e^{CHP}	2		\overline{SOC}^{EV}	100%
DW	\overline{P}^{DW}	0.42	REF	$\overline{P}_{t,e}^{REF}$	0.12
HHW	$\overline{P}_{t,e}^{HHW}$	0.5		\overline{T}^{REF}	9
	T_{INI}^{HHW}	18		\underline{T}^{REF}	3
	\underline{T}^{HHW}			T_{INI}^{REF}	27
	T^{INC}	6		T^{INI}	6
	\underline{T}^{HHW}	36			
Natural gas	π_t^{NG}	0.0120760	TES	\overline{P}^{TES+}	14.4
DR	k_e	5		\underline{P}^{TES+}	0
	k_t	5		\overline{P}^{TES-}	14.4
				\underline{P}^{TES-}	0

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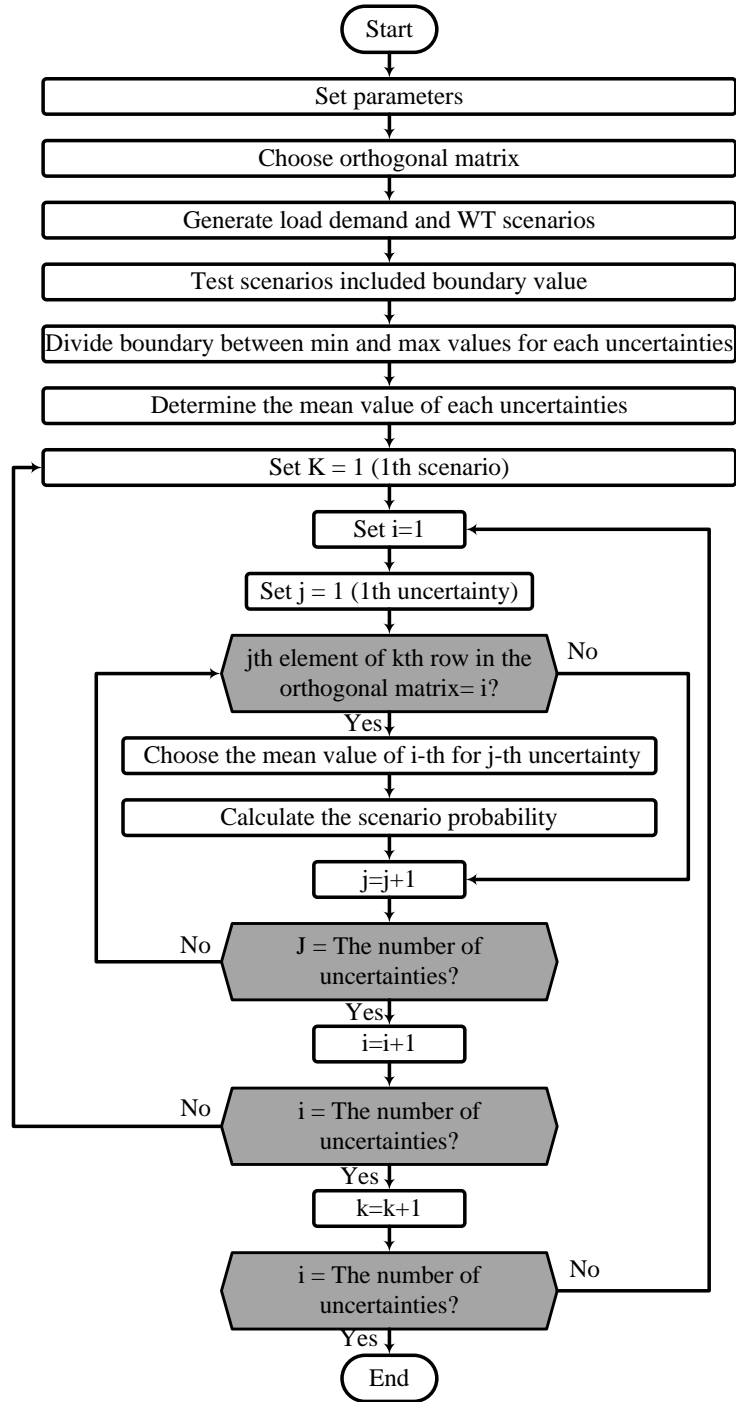


Figure 3: Uncertainty unit based on TOAT method

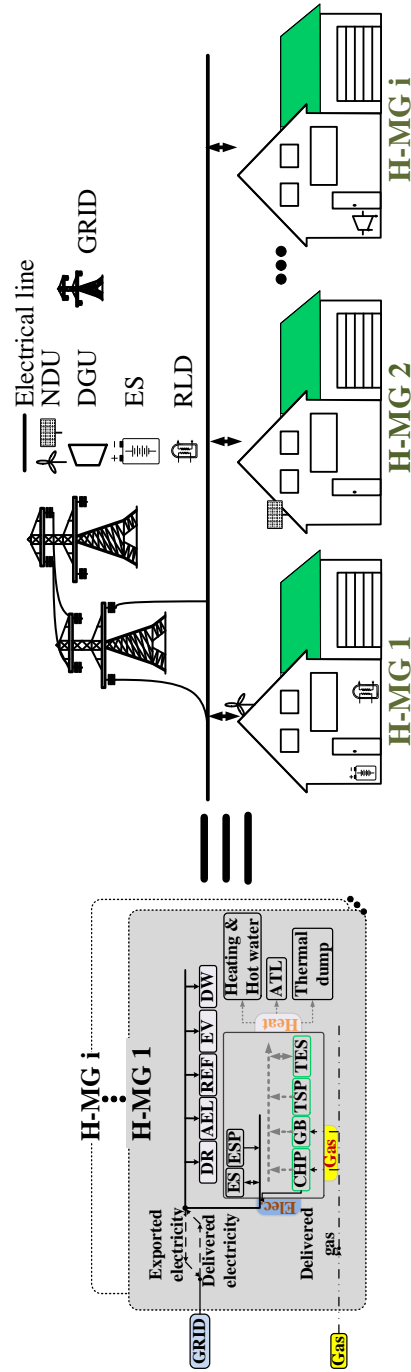


Figure 5: The schematic of neighbourhood system with several H-MGs (solid black lines show the electrical part, gray dash shows the thermal part and the dash-point is related to gas branch)

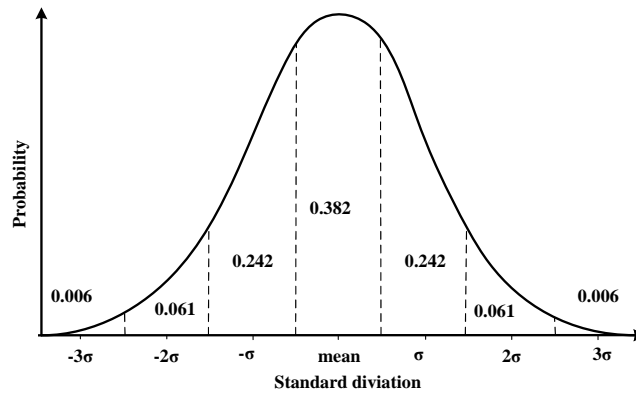


Figure 6: Seven-segment normal probability distribution curve

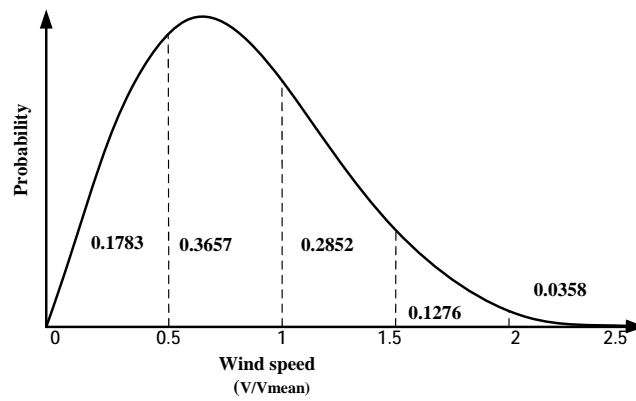


Figure 7: Wind speed probability distribution

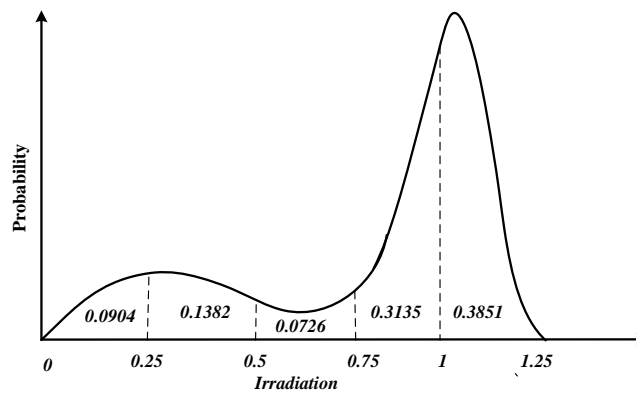
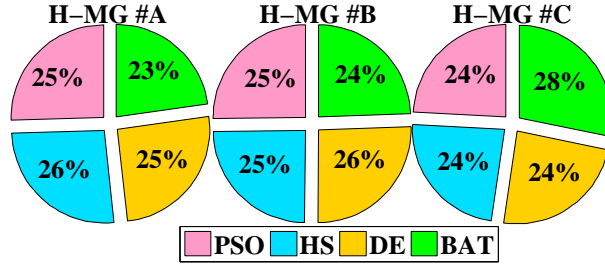
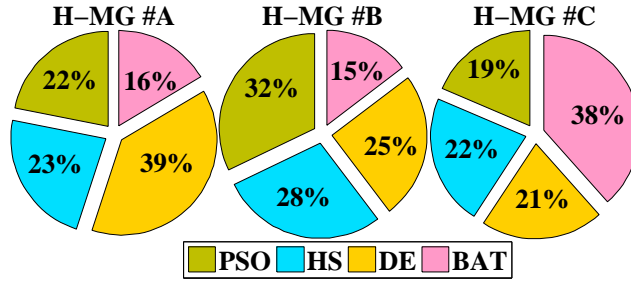


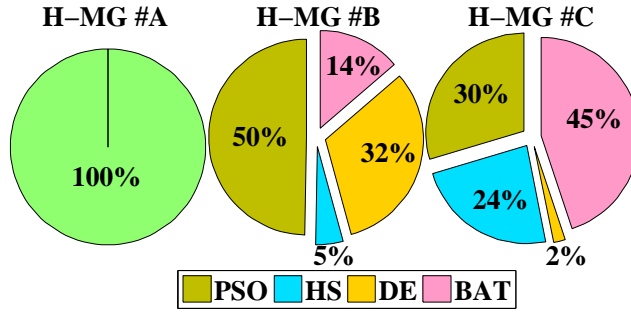
Figure 8: Solar radiation probabilistic distribution



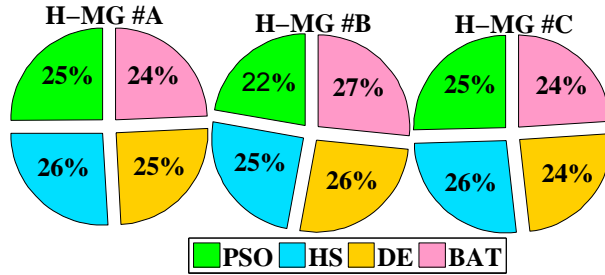
(a) The total generated power in each H-MG



(b) The electrical power sold by the H-MGs to the retailers

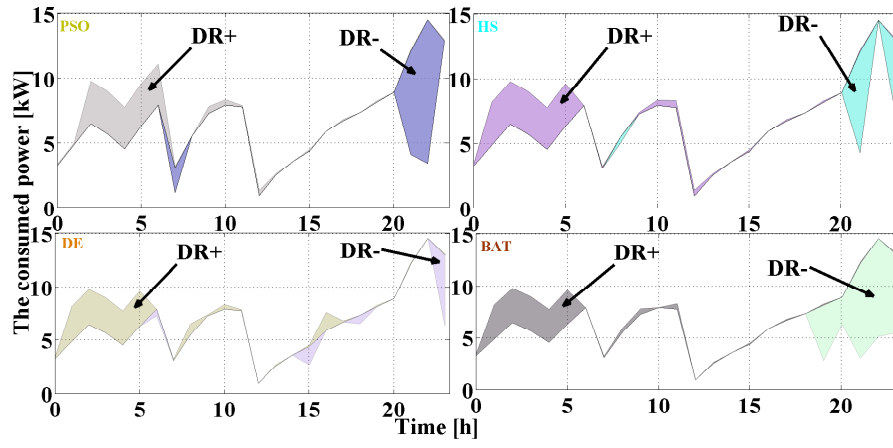


(c) The electrical power bought by the H-MGs from the retailers

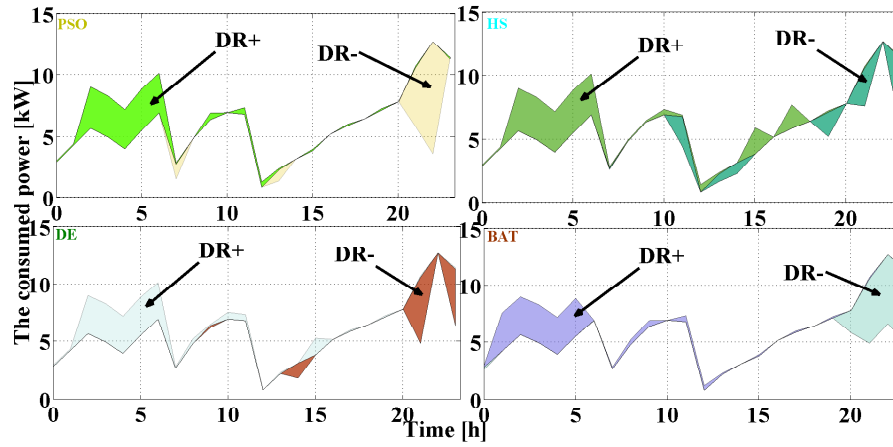


(d) The total generated thermal power in each H-MG

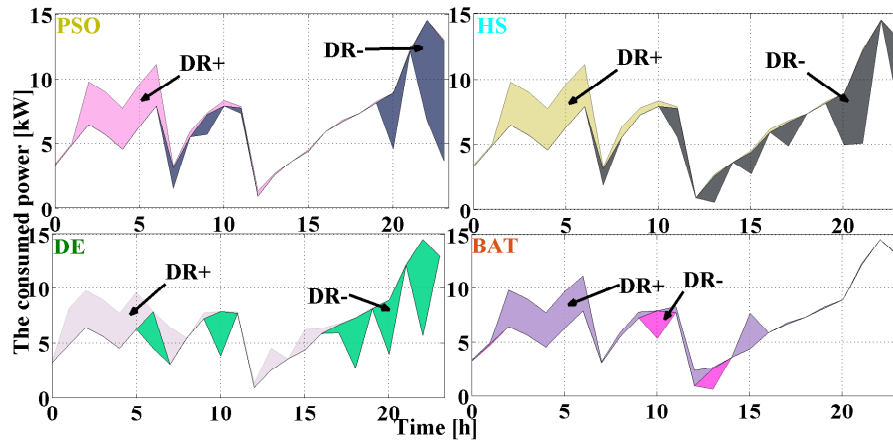
Figure 9: The electrical and thermal powers consumed by each H-MG using different optimization methods



(a) H-MG #A

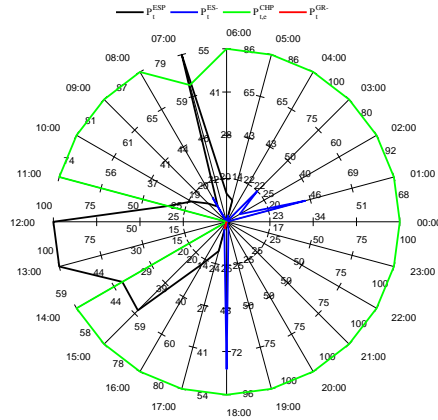


(b) H-MG #B

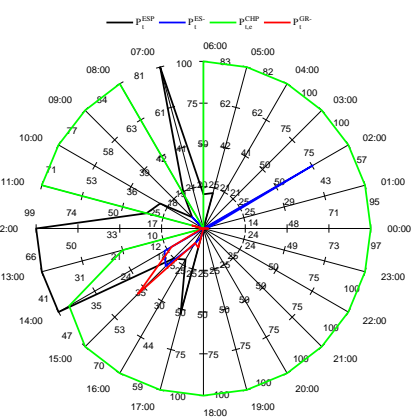


(c) H-MG #C

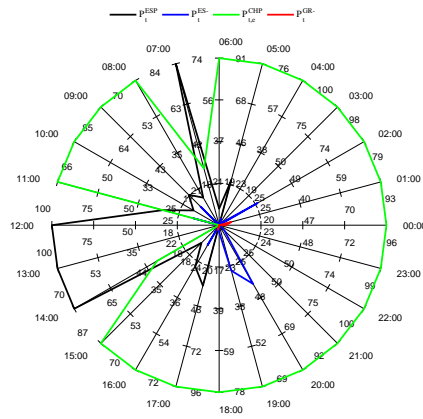
Figure 10: The consumed load demand profile in the H-MGs



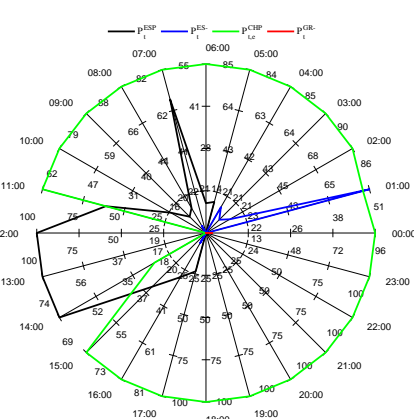
(a) BAT method



(b) DE method

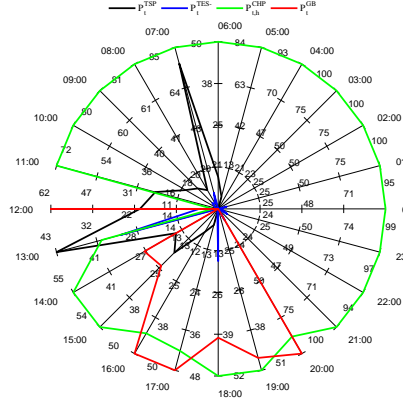


(c) HS method

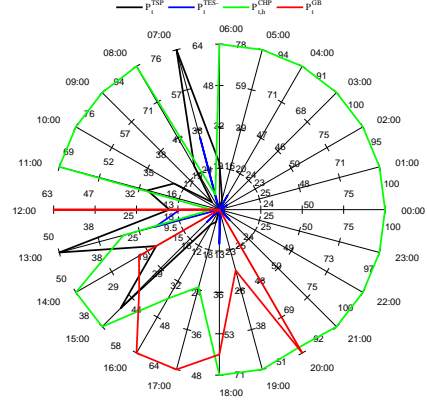


(d) PSO method

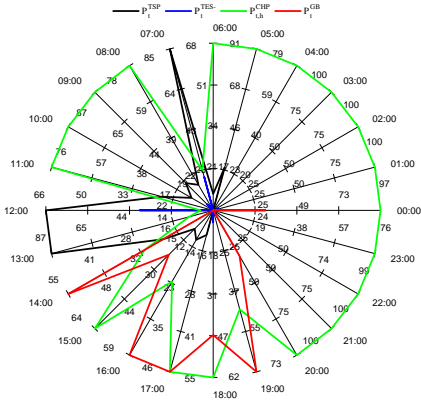
Figure 11: Electrical power percentage generated by the generation resources existing in the H-MGs based on BAT, DE, HS and PSO algorithms



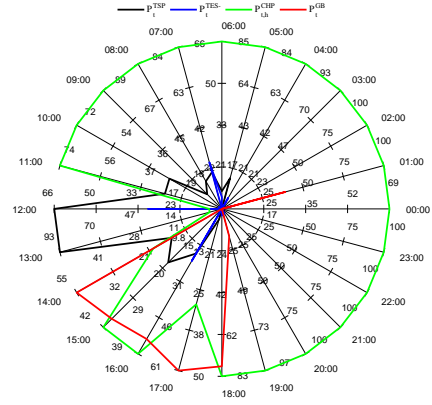
(a) BAT method



(b) DE method

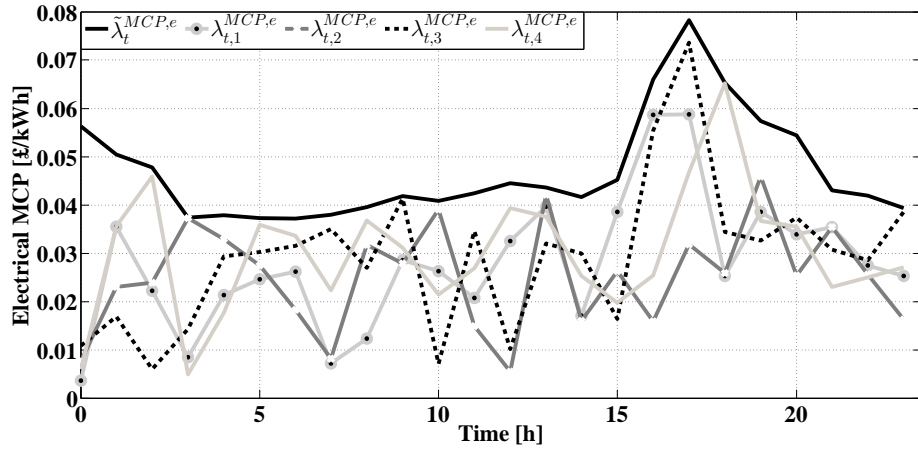


(c) HS method

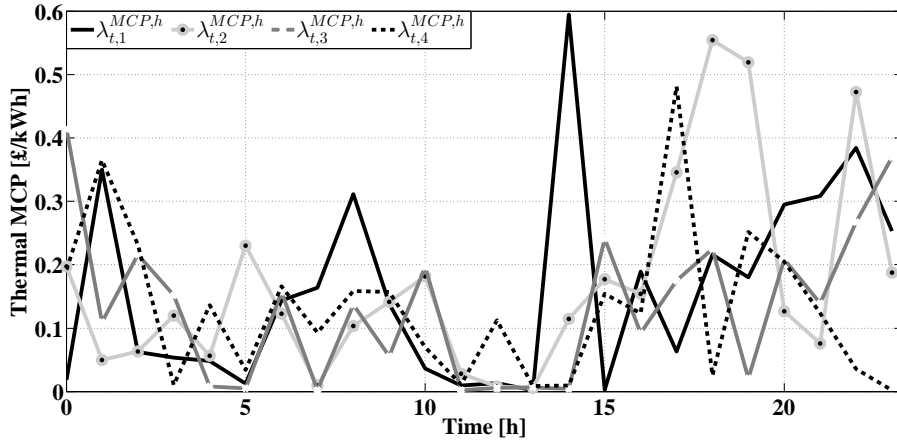


(d) PSO method

Figure 12: Thermal power percentage generated by generation resources based on BAT, DE, HS and PSO



(a) Electrical MCP



(b) Thermal MCP

Figure 13: MCP profile for the 24h performance of the system under study using different optimization methods

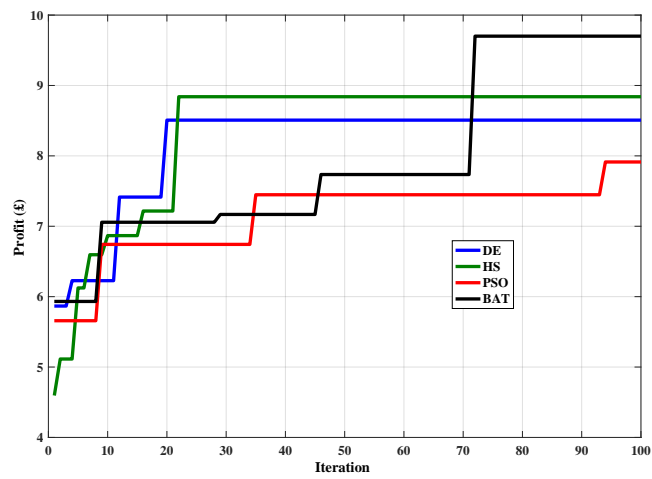


Figure 14: Convergence characteristics of the proposed algorithms